

Air quality impacts of plug-in hybrid electric vehicles in Texas: evaluating three battery charging scenarios

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Abstract

The air quality impacts of replacing approximately 20% of the gasoline-powered light duty vehicle miles traveled (VMT) with electric VMT by the year 2018 were examined for four major cities in Texas: Dallas/Ft Worth, Houston, Austin, and San Antonio. Plug-in hybrid electric vehicle (PHEV) charging was assumed to occur on the electric grid controlled by the Electricity Reliability Council of Texas (ERCOT), and three charging scenarios were examined: nighttime charging, charging to maximize battery life, and charging to maximize driver convenience. A subset of electricity generating units (EGUs) in Texas that were found to contribute the majority of the electricity generation needed to charge PHEVs at the times of day associated with each scenario was modeled using a regional photochemical model (CAMx). The net impacts of the PHEVs on the emissions of precursors to the formation of ozone included an increase in NO_x emissions from EGUs during times of day when the vehicle is charging, and a decrease in NO_x from mobile emissions. The changes in maximum daily 8 h ozone concentrations and average exposure potential at twelve air quality monitors in Texas were predicted on the basis of these changes in NO_x emissions. For all scenarios, at all monitors, the impact of changes in vehicular emissions, rather than EGU emissions, dominated the ozone impact. In general, PHEVs lead to an increase in ozone during nighttime hours (due to decreased scavenging from both vehicles and EGU stacks) and a decrease in ozone during daytime hours. A few monitors showed a larger increase in ozone for the convenience charging scenario versus the other two scenarios. Additionally, cumulative ozone exposure results indicate that nighttime charging is most likely to reduce a measure of ozone exposure potential versus the other two scenarios.

Keywords: PHEVs, ozone, air quality, DDM, charging, ERCOT

1. Introduction

Despite more than 30 years of emission reductions, some of the most densely populated regions in the United States

still fail to attain the National Ambient Air Quality Standards (NAAQS) for ozone, including many regions of Texas. Two of the largest sources of emissions that lead to ozone formation are vehicles and electricity generating units (EGUs). Increasingly, these two emission source categories are becoming intertwined, through the use of plug-in hybrid electric vehicles (PHEVs).

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PHEVs are capable of running on either electricity or gasoline. When operating on electricity, PHEVs have no tailpipe emissions. However, emissions are released when fuel is burned to generate electricity at power plants for charging these vehicles. While a number of analyses have been performed to assess the air quality implications of PHEVs, most of these analyses have examined only emission reductions (Jansen *et al* 2010, Kintner-Meyer *et al* 2007, Knipping and Duvall 2007a, Stephan and Sullivan 2008). A few studies (Thompson *et al* 2009, Brinkman *et al* 2010) have examined the impacts on ozone formation of the changes in spatial and temporal patterns of emissions that are the consequence of shifting emissions from fuel burning vehicles to fuel burning EGUs. However, these studies have considered relatively simplistic models of the distribution of additional EGU power generation (e.g., in Thompson *et al* 2009 assuming all charging occurs at night at only coal-fired power plants). This work examines the impact of three electricity dispatching scenarios that could occur as electricity demand increases with increased use of PHEVs. The scenarios to be considered in this work assume that the PHEVs are charged from the portion of the grid managed by the Electricity Reliability Council of Texas (ERCOT). The Texas grid makes for a particularly compelling geographical testbed because (1) it is well isolated from the rest of the nation's grid system, (2) it is large enough (serving 85% of the population and 75% of the area of Texas) to serve as a reasonable proxy for national electricity consumption while remaining small enough to model effectively, (3) it has more installed wind power than any other state and that wind blows strongly at night, which opens up the prospects for emissions-free charging of some portion of electric vehicles, (4) Texans drive more miles than Americans on average, and (5) Texas experiences many episodes of high ozone concentrations. The distribution of electricity generation capacity (MW) in this grid, by type of fuel, is 20% coal, 71% natural gas, 5% nuclear and 4% wind (EIA 2010a), while in 2009 the shares of actual electricity generation in ERCOT were 46% natural gas, 35% coal, 13% nuclear, and 4.5% wind (EIA 2010b).

The Pacific Northwest National Laboratory (PNNL) found that the existing capacity within ERCOT, if fully utilized 24 h a day, is capable of supporting a switch of 100% of light duty vehicles to PHEVs (Kintner-Meyer *et al* 2007). Light duty vehicles in this case include all passenger cars, light duty trucks, SUVs and vans. While the PNNL study also reported that a switch to PHEVs of 100% of light duty vehicles would decrease emissions of GHGs, NO_x, SO_x, VOC, CO and PM₁₀, no air quality modeling was done. Because the chemistry of ozone formation can be very sensitive to even small changes in timing or location of precursor emissions, shifting emission sources from urban, daytime tailpipes of gasoline-powered cars to (often) rural, stacks of power plants burning coal or gas can have a significant impact on photochemical air pollutant formation. Consequently, just determining the differences in direct emissions does not reveal the complexity of air quality issues. This work will address this knowledge gap and expand on prior analyses by examining the impacts PHEV charging patterns, and the effect of the increased demand on which EGUs are operated (dispatching order), on air quality in Texas.

In most cases, charging PHEVs at night is the best case scenario for electricity grids in terms of reliability and cost-effectiveness because there is often a decrease in electricity demand at night and therefore excess capacity (Jansen *et al* 2010, Martin *et al* 2007). Nighttime excess capacity can also mean that electricity is cheaper at night. It is likely, however, that unless policies are put into place to force nighttime charging, other factors will influence the charging profiles (Lemoine *et al* 2008). This study will examine nighttime charging as well as charging profiles based on convenience to the vehicle user and optimization of battery lifetime.

2. Air quality modeling methods

2.1. Modeling episode

The air quality impacts of shifting emissions from vehicles to electricity generating units (EGU) will be examined using a 3D Eulerian photochemical grid model. The model predicts the spatial and temporal movement, production and depletion of air pollutants using data on emissions, meteorology, chemistry and deposition. Several such models, approved for regulatory applications in the United States, are available. The model to be used in this work is the Comprehensive Air Quality Model, with extensions (CAMx, www.camx.com). CAMx was chosen for this work because of the availability of meteorological, land cover, boundary condition, initial condition and emission inputs for air pollution episodes in Texas, and because the State of Texas uses CAMx in its air quality management decision-making.

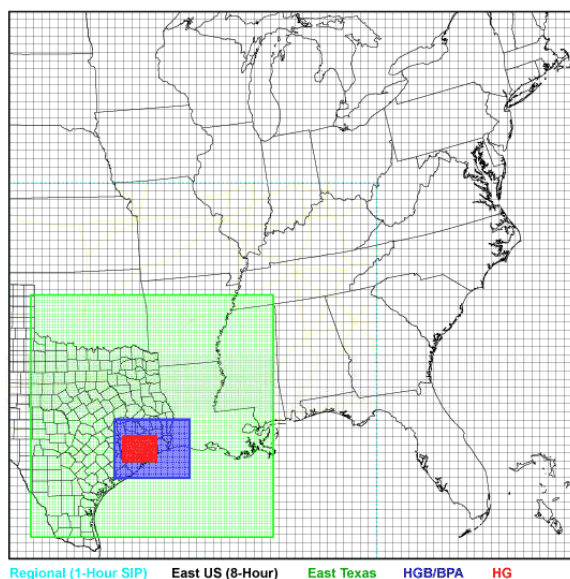
Air quality models are used to demonstrate the potential of air quality management plans to attain National Ambient Air Quality Standards, and the air quality modeling episode to be used for this study was developed by the Texas Commission on Environmental Quality (TCEQ) to demonstrate that the Houston–Galveston–Brazoria area (HGB) would attain the ozone NAAQS by 2018. The base case of the PHEV modeling will be the air quality modeling with anticipated emissions by 2018 (with federally mandated emission controls but no additional local controls) developed by the TCEQ. In this base case, no changes are made to the vehicle or EGU emissions. The details of this episode are found in the report titled 'Emissions Modeling for the HGB Attainment Demonstration SIP Revision for the 1997 Eight-Hour Ozone Standard' (TCEQ 2010a). The model inputs are available from the TCEQ (2010b). The meteorological inputs represent actual conditions during the summer of 2006 while the emissions inventories reflect predicted emissions in 2018. The episode runs from 13 August to 15 September. Figure 1 shows the modeling domain with 36 km grid cells, as well as the nested 12, 4, and 2 km grids.

2.2. Point sources

Power plant emissions inventories, as developed for the 2018 Houston attainment demonstration, are based on 2006 actual emissions and forecast to the year 2018 based on the previous EPA/State of Texas' Clean Air Interstate Rule (CAIR) allocations (TCEQ 2010a). Baseline inventories for

Table 1. Distribution of VMT and NO_x emissions to total vehicles, light duty gasoline vehicles (LDGVs), and PHEVs. All values are daily totals.

County	2018 total daily VMT (all vehicle types)	LDGV % of total VMT (%)	PHEV daily VMT (20% of LDGV)	2018 total daily NO _x (tons)	LDGV % of total NO _x (%)	Daily NO _x reductions from mobile emissions due to PHEV use (tons)
Bexar	44 675 409	59.9	5348 851	23.03	35.1	1.62
Dallas	85 064 855	65.6	11 166 505	24.5	36.6	1.79
Travis	30 675 154	63.1	3869 112	8.94	35.7	0.64
Harris	122 810 170	61.2	15 030 463	33.3	33.6	2.24
Tarrant	58 190 356	61.0	7099 399	18.63	30.6	1.14
Total	341 415 944	62.3	42 514 330	108.39	34.2	7.42

**Figure 1.** 36 km (black), 12 km (green), 4 km (blue), and 2 km (red) grid domains (TCEQ 2009).

power plants existing as of 2009 are determined from the US EPA's 2006 Acid Rain Database (EPA 2006). The emissions inventories for new or proposed plants are based on permit applications, with average temporal profiles assigned based on facility type.

The final CAMx-ready point source input file was developed by TCEQ, and obtained from the TCEQ in May of 2010 (TCEQ 2010b). Individual emissions stacks at each power plant are identified by spatial coordinates, and stack parameters.

2.3. Mobile sources

The on-road mobile emissions inventories were developed using the US EPA's on-road mobile source emissions modeling program MOBILE6.2 (EPA 2003). Within the HGB 2 and 4 km grid domain, link-based emissions inventories (EIs) were developed that provide emissions along each roadway link (TCEQ 2010a). The remaining areas in Texas, including San Antonio, Dallas and Austin are modeled using a 12 km spatial domain and virtual link data. Virtual links are estimates of the number, spatial distributions, and VMT of the various links within each county. VMT for areas outside of Houston

are based on county-level Highway Performance Monitoring System (HPMS) data (TCEQ 2010b). More details about the development of non-HGB mobile EIs is available from the Texas Transportation Institute (TTI 2006).

Estimates were made of the decreases in mobile emissions from the substitution of 20% of light duty gasoline vehicles (LDGVs) vehicle miles traveled (VMT) with electric VMTs using PHEVs in five large urban counties. These counties were Bexar (San Antonio), Dallas (Dallas), Harris (Houston), Travis (Austin) and Tarrant (Fort Worth). All other mobile source emissions remain unchanged. For this study, SUVs and light trucks were not included. LDGVs include only passenger cars.

While light duty vehicles account for 63% of the total VMT, they only account for 34% of the NO_x emissions from mobile sources, on average, in the five counties of interest in Texas (Bexar, Dallas, Harris, Travis and Tarrant). Therefore, mobile NO_x emissions were only reduced by 6.8%, despite a 20% substitution, equal to an estimated total reduction across all five counties of 7.42 tons day⁻¹. Table 1 outlines the distribution of VMT and NO_x reductions to the five counties of interest. In most cases, previous air quality modeling of Texas has found ozone concentrations in Texas to be primarily sensitive to NO_x emission reductions (Nowlin 2001, Nobel *et al* 2001, Thompson and Allen 2010). For this reason, this study evaluated the sensitivity of ozone to NO_x changes only.

3. PHEV charging scenarios

An additional 13 528 MWh day⁻¹ would be required to support a switch of 20% of LDGV VMT to electric VMTs in Dallas, Tarrant, Harris, Travis and Bexar counties. This magnitude corresponds to 42.5 million miles day⁻¹ of PHEV use assuming a fuel economy value of 318.2 Wh mile⁻¹ (Knipping and Duvall 2007b).

There is much debate on what an ideal charging profile might be, and how best to guide PHEV owners towards that ideal (Jansen *et al* 2010, Kintner-Meyer *et al* 2007, Lemoine *et al* 2008, Knipping and Duvall 2007a, Stephan and Sullivan 2008). For this study, three charging profiles were modeled. The first profile represents charging during off-peak driving hours, primarily at night with limited charging at mid-day (Knipping and Duvall 2007a). This charging scenario will be referred to as 'night' (night). The second profile was motivated by increasing battery life (battery). In order to prolong the life of a battery, charging should occur just before use, and

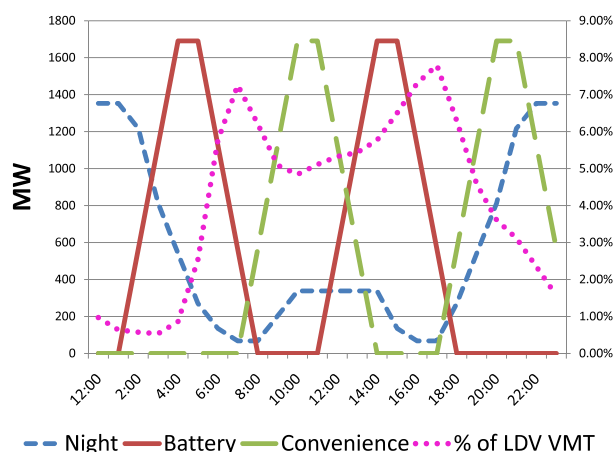


Figure 2. Diurnal charging profiles for three PHEV scenarios (left axis) plus diurnal profile of light duty vehicle miles traveled (VMT) as a percentage of total VMT (right axis).

only as much as needed (Bashash *et al* 2011). This charging scenario has higher electricity demand before the morning and evening driving peaks. The final profile represents a charging profile that is assumed to be convenient for the driver (convenience). For this scenario, charging occurs immediately after peak driving hours, and assumes that drivers immediately plug-in their vehicles after arriving at a location (Lemoine *et al* 2008). Diurnal profiles of electricity use for these three charging scenarios are shown in figure 2. In both the ‘battery’ and ‘convenience’ scenarios, the total MWhs needed to charge PHEVs are split equally into two charging peaks.

4. Modeling of electricity dispatching

Electricity grid modeling was conducted with actual dispatch data for the highest demand day of 2009, 13 July 2009. Then, new power plants planned to be installed by 2018 were added to the list of EGUs to generate a dispatch order for the modeled future simulation peak day in 2018. The peak demand in 2018 is assumed to be 74 418 MW based upon ERCOT projections from 2008 (ERCOT 2009). Figure 3 shows the dispatching assumed for this future case peak demand day. All ‘new’ EGUs assumed to be installed after 13 July 2009 and before ‘13 July’ 2018, are included in the analysis by assigning an average generation profile for the specific fuel and unit type combinations. For example, a new natural gas combined cycle (NGCC) plant is assumed to act just as the average NGCC plant in the ERCOT grid.

Computational and analytical challenges were associated with choosing the marginal power plants that contribute to charging PHEVs. For example, there are several dozen EGUs that are candidates for ramping up to charge PHEVs in any given hour of the day. Additionally, the same set of EGUs are not candidates in each hour. This diversity is to be expected as approximately 580 EGUs are modeled and each EGU acts relatively independently of the others. Modeling the air quality impacts from the marginal emissions of 20–60 different EGUs each hour of the day was not practicable for this work, and

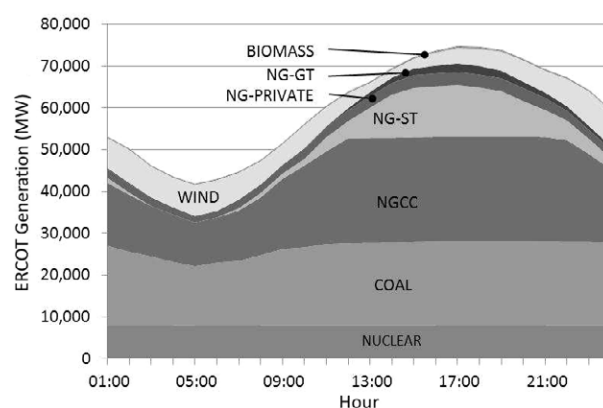


Figure 3. The hourly dispatch of different types of power plants in 2018 is based upon the peak day in 2009. Natural gas–gas turbine (NG–GT), natural gas–steam turbine (NG–ST), natural gas combined cycle (NGCC).

an alternate approach for selecting the EGUs for air quality modeling was chosen.

The approach used in this work is as follows. The total daily generation needed to charge PHEVs for traveling 20% of LDV miles on electricity is 13 528 MWh. Of that daily total, between 2500 and 4500 MWh day^{−1} comes from non-emitting power plant sources (nuclear, wind, water or solar but primarily wind in the cases considered in this work), depending on the charging scenario. The remaining generation needed to charge PHEVs, ~9000–11 000 MWh day^{−1}, comes from power plants that emit air pollutants. For each hour of PHEV charging, the change in total generation from the previous hour is calculated to determine the hour-specific ramp rate for the entire ERCOT grid. The EGUs are then ordered from lowest (negative) to highest (positive) ramp rate. Then all of the EGUs that are ramping in the same direction as all of ERCOT (i.e. if total ERCOT load is rising we choose only EGUs that are ramping up, and vice versa) are chosen as the subset of EGUs that can ramp up to account for the additional electricity demand for charging EVs at that hour. Using this procedure, it was found that 84, 99, and 144 emitting power plants would contribute to PHEV charging for the convenience, battery, and night scenarios, respectively. However, in each case, there is a smaller group of plants that contribute the majority of the electricity needed. The emitting plus non-emitting power plants that together account for 80% of the electricity needed to charge PHEVs each day were identified. These highest-contributing power plants number 20, 28, and 45 for the convenience, battery, and night scenarios, respectively. Air quality modeling tools were used to model the sensitivity of ozone formation to NO_x emissions from these top-contributing power plants. The NO_x emissions due to PHEV charging for all of these plants were assumed to have the same temporal pattern, shown in the charging profiles illustrated in figure 2. The emissions were scaled so that, collectively, the modeled EGUs accounted for the entire 13 528 MWh day^{−1} needed to charge PHEVs. The names and locations of emitting EGUs found to contribute to 80% of the daily generation needed for PHEV charging in all three scenarios are shown in figure 4.

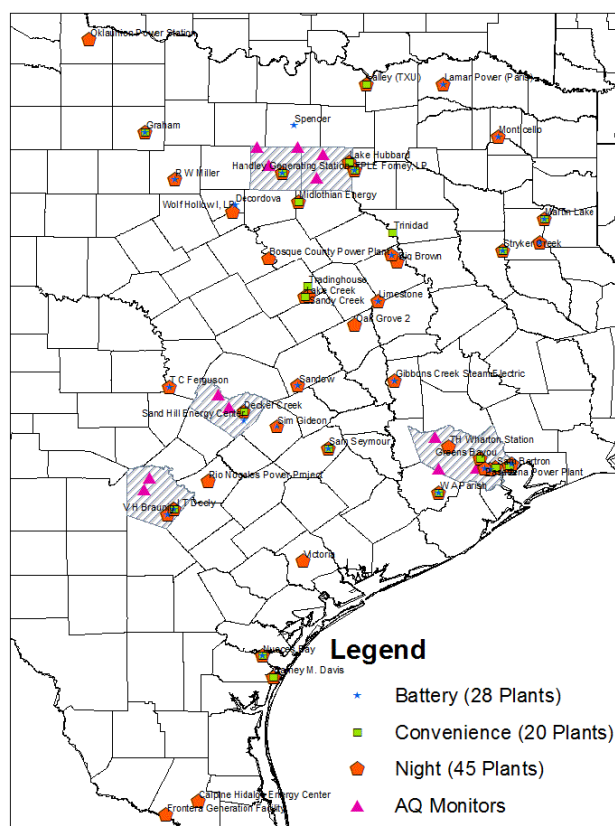


Figure 4. The locations of air quality monitors (receptors), along with the dispatched EGU's identified as contributing to PHEV charging, are modeled using DDM for the three charging scenarios.

The air quality monitors which were selected as indicators of air quality changes are also shown in figure 4.

5. Photochemical modeling with DDM

The decoupled direct method (DDM) is a tool within CAMx that is used to calculate the first order coefficients that represent the sensitivity of pollutant concentrations at user-defined locations, to small changes in emissions from any source (Environ 2008). For this work, the changes in ozone concentrations at air quality monitor locations throughout Texas (receptors) were evaluated, when specific power plants increase electricity generation in order to charge PHEVs (sources). The sensitivity coefficients generated for this study represent dO_3/dNO_x . Twelve air quality monitors are chosen as receptors for this evaluation. These sites generally represented the sites with the highest peak 8 h averaged ozone concentrations in each of the urban areas considered in this work. The locations of these twelve monitors are shown in figure 4.

In this analysis, increases in electricity demand were estimated for specific EGU facilities, however, some individual facilities might have multiple boilers or power generation units, with different emission characteristics. In these cases, the contributions from individual units are summed and modeled as one single contribution and the tallest contributing stack at the facility is modeled in CAMx. DDM was run for 8

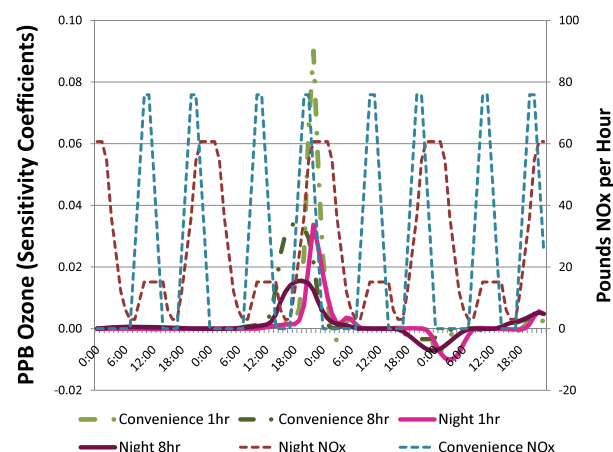


Figure 5. Profile of NO_x emissions from a high NO_x natural gas unit and resulting impact (sensitivity coefficients) on 1 and 8 h average ozone concentrations at Grapevine monitor in DFW for both the convenience and night scenarios over the course of the four day episode.

September to 13 September. The first two days are spin up days, and are not evaluated. Sensitivity coefficients are calculated for Sunday 10 September to Wednesday 13 September. These dates were chosen because, for each of the four regions of interest, they contain a wide range of maximum 8 h ozone concentration predictions. The maximum 8 h average ozone concentration on 11 September is one of the three highest values modeled from the entire month-long episode, for all four regions, and is greater than 100 ppb in both Dallas and Houston and greater than 70 in Austin and San Antonio. Ozone concentrations on 10 September are also above 70 ppb, while 12 and 13 September represent relatively low ozone concentrations, falling below 60 ppb at most monitors.

5.1. Sample results

CAMx DDM runs are set up such that the sensitivity coefficients calculated by the model, for each of 12 monitoring sites (receptors), represent the change in ozone concentrations in each hour of each day per increase of 100 MWh of generation per day (and the associated NO_x emissions) from a single EGU. The change in NO_x emissions required for an increase of 100 MWh generated at each EGU over the course of a day are based on time averaged NO_x emission rates for each EGU available on EPA's eGRID site (EPA 2007). The NO_x emissions modeled in DDM are distributed in a diurnal profile in proportion to the corresponding charging scenario (see figure 2). So, for example, if an EGU was found to contribute ~300 MWh (per day) to the 'nighttime' scenario, the sensitivity of ozone formation for each hour per 100 MWh at each receptor site was multiplied by 3. The 1 h ozone sensitivities are then averaged over 8 h to get the sensitivity of 8 h ozone concentrations at any given receptor site. The sensitivities of 1 h averaged and 8 h averaged ozone concentrations at one site (Grapevine, near Dallas) to 100 MWh changes in one EGU (a natural gas unit that has high

NO_x emissions per unit energy input) are shown in figure 5 for two charging scenarios. The high NO_x natural gas unit is found to increase the 1 h ozone average by 0.09 ppb at 8:00 PM on 11 September at the Grapevine monitor due to 100 MWh of PHEV charging in the convenience scenario. If this EGU actually contributes 600 MWh to convenience charging, the resulting increase of 1 h ozone at the Grapevine monitor will be 0.54 ppb (6×0.09 ppb).

In February 2011, the EPA released updated eGRID data, based on 2007 emissions rates (EPA 2011). The following analysis was re-evaluated using the 2007 eGRID data and is available upon request. Results were very similar to those reported in this paper.

The results shown in figure 5 are expected based on meteorological conditions and the location of the high NO_x natural gas unit relative to the Grapevine monitor. On 10 September and the early part of 11 September, the wind is southerly and EGU is downwind of Grapevine, therefore having no impact on air quality at that monitor. During the early evening hours of 11 September, wind direction begins to change to northerly instead of southerly. Initially there is a short period of calm, almost stagnant air with a slight northerly flow, and that is when the sensitivity to emissions from the EGU increase dramatically. Then as the northern winds speed up, sensitivity of ozone at Grapevine to the EGU emissions decreases. During nighttime hours on 12 September, the EGU emissions are shown to scavenge (decrease) ozone at Grapevine.

5.2. Scaling EGU contributions to NO_x emissions for PHEV charging

The DDM sensitivities allow for a direct comparison of the relative contributions of the EGUs charging PHEVs, however the goal in this work is to estimate, for each scenario, the cumulative contribution of all EGUs to ozone. The total expected change in ozone at each monitor can be calculated by summing the weighted sensitivity coefficients from each of the contributing power plants (data similar to what is shown for a single EGU in figure 5) plus the mobile contribution. Sensitivity coefficients represent emissions associated with 100 MWh, but the total generation necessary to charge PHEVs to substitute for 20% of Light Duty Gasoline Vehicle VMT is 13 528 MWh. Therefore in order to fully account for PHEVs, some combination of the sum of 135.3 contributions of 100 MWh generation sensitivities is needed.

The total change in ozone concentration is calculated by scaling the projected 13 July 2018 electricity generation contribution of each power plant to PHEV charging. For example, a natural gas-fired power plant in Fort Bend Co, was estimated to contribute 698 MWh day⁻¹ to the charging of PHEVs in the convenience scenario when all power plants were considered. That is 11.2% of the total contribution of the subset of 20 power plants modeled using DDM. Non-emitting sources contribute 4592 MWh day⁻¹ in the 'convenience' scenario, and subtracting that quantity from the total daily generation needed to charge PHEVs (13 534 MWh) leaves 8943 MWh needed from those 20 power plants. Therefore, the emissions

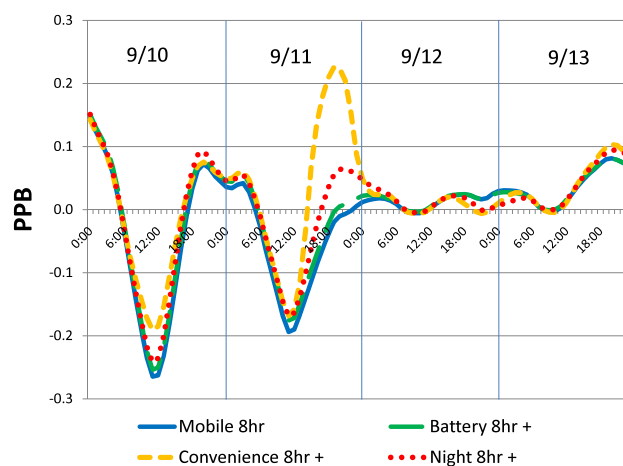


Figure 6. Time series of impacts to the 8 h average ozone concentration at Grapevine monitor (DFW) due to NO_x emissions changes associated with charging and driving PHEVs.

from the Fort Bend plant is assumed to generate 1000 MWh, or 11.2% of 8943 MWh, and therefore this plant contributes an ozone concentration to each monitor that is 10 times the sensitivity coefficients generated by DDM.

Weighting factors, representing the relative daily contribution of each EGU to PHEV charging, were calculated for each scenario. Using these factors, the total hourly change in ozone due to increased emissions from charging is calculated as shown in equation (1). Alternate factors can also be calculated to represent other charging scenarios.

$$\partial O_{3,h,m} = \sum_{i=1}^n \text{factor}_i \times \text{sensitivity coefficient}_{i,h,m}, \quad (1)$$

where: factor = (estimated MWh required to meet PHEV demand/100 MWh of generation) \times NO_x emissions for generation of 100 MWh, sensitivity coefficient = output from DDM of dO_3/dNO_x per facility, per hour, for each receptor site m , assuming generation of 100 MWh, m = air quality monitor (a total of 12 are evaluated for this study) h = 0–23, hours of the day n = number of EGUs contributing to PHEV charging (20, 27, and 45 for the convenience, battery, and night scenarios, respectively to account for the required PHEV charging).

The total hourly change in ozone due to increased emissions from charging as calculated using equation (1), is then added to the hourly change in ozone due to decreased emissions from light duty vehicles. Those values are then averaged over 8 h to get the total hourly change to 8 h averaged ozone concentrations at each monitor, for each scenario. These values are shown in figures 6–10 for scenarios convenience, battery, and night. The same weighting factors were used with average NO_x emissions factors available on EPA's eGRID (EPA 2007) to calculate the total NO_x emissions increases associated with PHEV charging for each scenario. According to the weighting factors, 4.0, 5.5 and 6.3 tons of NO_x were emitted in order to charge PHEVs following the convenience, battery, and night charging scenarios respectively, relative to the 7.4 tons day⁻¹ of NO_x decreased from mobile sources.

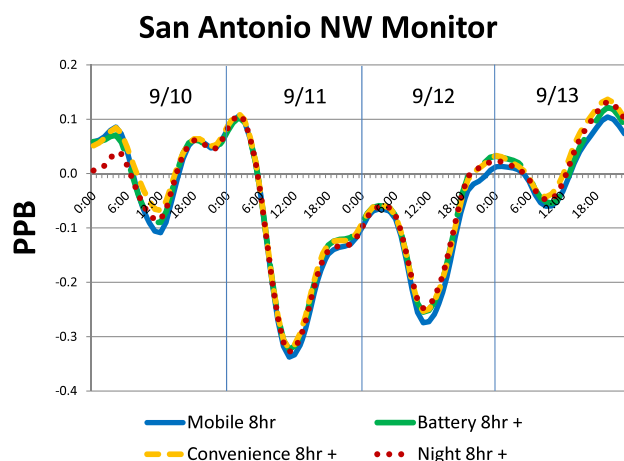


Figure 7. Time series of the change in the 8 h average ozone concentration at a San Antonio air quality monitor, due to PHEVs.

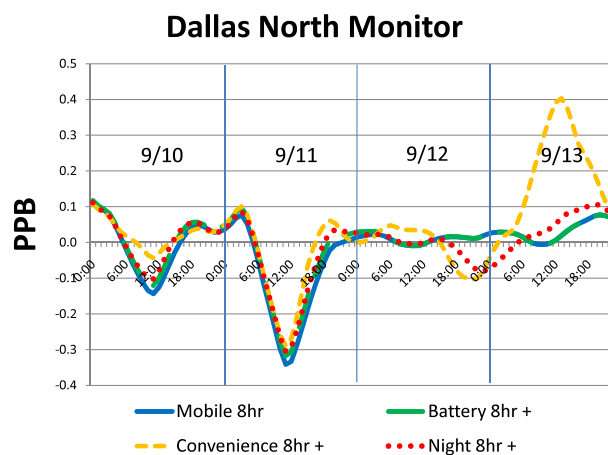


Figure 9. Time series of the change in the 8 h average ozone concentration at a Dallas air quality monitor, due to PHEVs.

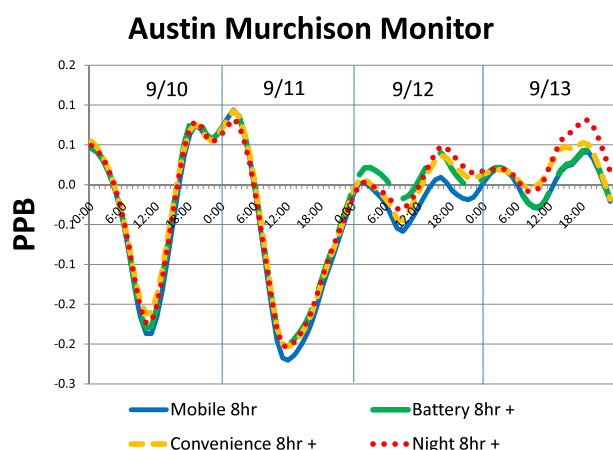


Figure 8. Time series of the change in the 8 h average ozone concentration at an Austin air quality monitor, due to PHEVs.

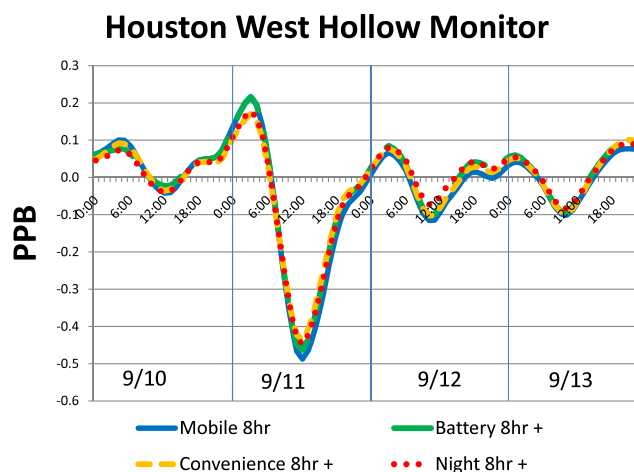


Figure 10. Time series of the change in the 8 h average ozone concentration at a Houston air quality monitor, due to PHEVs.

6. Results

The impact of PHEVs on ozone is dominated by the impact associated with mobile NO_x emissions decreases. Figure 6 shows the change in 8 h average ozone concentration at Grapevine monitor, due to PHEVs. Negative values indicate 8 h average ozone concentrations are decreasing due to PHEVs. The impact due only to decreases in NO_x emissions from mobile sources is shown in blue. Incorporating the impact of NO_x emissions increases due to charging for the battery, convenience, and night scenarios are shown in green, yellow, and red respectively. The patterns closely follow that of mobile changes alone except at 8:00 PM on 11 September when the impact on ozone from the ‘convenience’ scenario increases relative to the other scenarios. This increase is driven by the contribution from a single high NO_x emitting EGU, shown in figure 5.

Figures 7–10 below present the results of the PHEV sensitivity study at four of the twelve monitors. Monitors not shown are well represented by results from the monitor

in the same city and are available in appendix B. In all cases, the impact is dominated by the mobile source impact. The general trend is to see decreases in 8 h averaged ozone concentrations during daytime hours, and increases in 8 h average ozone concentrations during nighttime hours. The decrease in daytime ozone due to PHEVs is larger during the first two days of the episode when ozone is forecast to be considerably higher. During the second two days of the episode, when ozone concentrations are relatively low, PHEVs increase 8 h ozone concentrations during all hours of the day. The max 8 h values are greater than 90 ppb in Dallas and Houston on 10 and 11 September, and only about 60 ppb and 70 ppb in Dallas and Houston, respectively, on both 12 and 13 September.

The daily maximum 8 h ozone concentration usually occurs between about 10 AM and 1 PM. As can be seen in figures 7–10, this is typically the time of day associated with maximum decreases in 8 h average ozone due to PHEVs. This means that PHEVs are likely to positively impact air quality

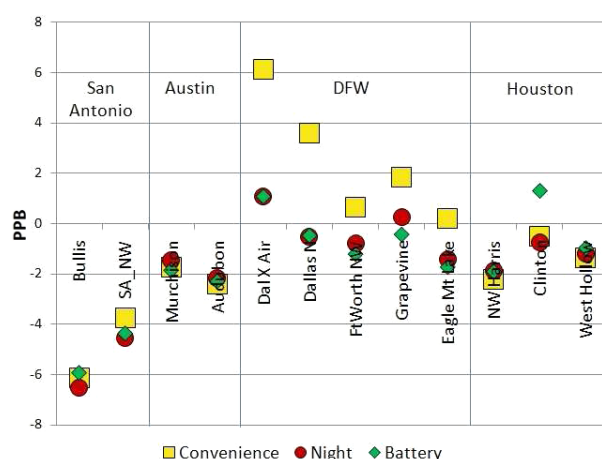


Figure 11. Cumulative change in 8 h ozone concentrations across all four days of the modeled PHEV episode, for each of the 12 monitors and 3 PHEV charging scenarios.

with regards to attainment of the 8 h ozone standard. And in fact, on average across all 12 monitors, and all three scenarios, the 8 h maximum ozone concentration is predicted to decrease by approximately 0.15 ppb.

Very little difference can be seen between the three charging scenarios in most of the figures. The exception is the final day of the episode at the Dallas North monitor during which the ‘convenience’ scenario air quality impacts are drastically different. 8 h averaged ozone in Dallas increases by 0.4 ppb due to PHEVs in the ‘convenience’ case relative to the other scenarios. This strong impact felt by Dallas monitors due to the ‘convenience’ charging scenario is due to a relatively slow northerly wind speed carrying NO_x emissions from a single EGU that is close to the city and has a high NO_x emissions factor.

In order to represent the impact of PHEVs on ozone exposure, the cumulative change in ozone concentrations across all four days of the PHEV episode, at each of the twelve monitors is calculated. For example, if 8 h ozone concentrations decrease by 0.1 ppb at 6 AM and increase by 0.1 ppb at 7 AM, the average of the two hours would be a zero change. Figure 11 shows the time integrated changes in ozone concentrations. While it is not possible to directly connect ambient ozone concentrations and human exposure, the cumulative change in ozone as shown in figure 11 is an approximation of how human exposure could change due to PHEVs.

Figure 11 shows that for all charging scenarios in San Antonio and Austin, potential exposure is reduced. The results are less clear in Dallas and Houston. It is clear however, that nighttime charging is the charging scenario most likely to minimize the negative impact of PHEVs on attainment and exposure in all cases in those two cities.

7. Conclusions

The potential air quality impact of PHEVs is dominated by the impact of the NO_x decreases from mobile sources. In most

cases the decrease in NO_x emissions due to PHEVs causes a decrease in 8 h average ozone concentrations during the day when the maximum value is likely to occur. The result is a likely decrease in the daily maximum 8 h average ozone concentration, the value used to determine attainment of the 8 h standard. The impact of PHEVs on ozone is largest on days forecast to have high ozone. This high ozone day impact is desirable for both attainment of regulatory standards and for exposure. Mobile source emissions decrease during nighttime hours often cause increases in nighttime ozone due to decreased scavenging of ozone by nighttime NO_x . Nighttime increases in ozone are less likely to impact humans because fewer people are awake and outside and therefore fewer people are being exposed to higher ozone during nighttime hours. Thus, the switch of 20% of LDV VMT from gasoline to electric travel shifts ozone formation to a time period that is likely less harmful to humans.

This study has shown that while in most cases there is little difference in maximum ozone concentrations between the air quality impacts of the three charging scenarios, the ‘convenience’ charging scenario is most likely to cause increases in daytime ozone. In contrast, changes in ozone concentrations integrated over the entire episode, showed greater differences between scenarios, with nighttime charging showing the best performance. While changes in greenhouse gas emissions have not been a focus of this analysis, it is worth noting that, using eGRID average carbon dioxide emissions factors (EPA 2007) and MOBILE6 CO_2 emissions totals (TCEQ 2010b), CO_2 emissions were estimated to decrease by about 17 000 tons day^{-1} due to mobile source decreases, and increase by 8000, 7000 and 7000 tons day^{-1} for the night, convenience and battery scenarios respectively. Therefore, the PHEV scenarios presented in this work would decrease CO_2 emissions by over half regardless of when they are charged.

Acknowledgment

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Appendix A. Back trajectories

The air quality modeling episode from 10 September to 13 September was chosen because of the range of predicted ozone concentrations, and also because it included a variety of wind patterns. Wind directions move from the southeast on 10 September, through the south on 11 September, and through the north on 12 and 13 September providing nearly the full range of wind directions and therefore, the full range of impacting (upwind) facilities. Figures A.1–A.4 show air parcel back trajectories for Austin, San Antonio, Houston, and Dallas, for each day of the modeling period. The back trajectories represent the path the air travels for the 48 h prior to arriving at each city. A separate trajectory is modeled for air parcels arriving in the targeted city by 10 AM, 12 PM, 2 PM, 4 PM,

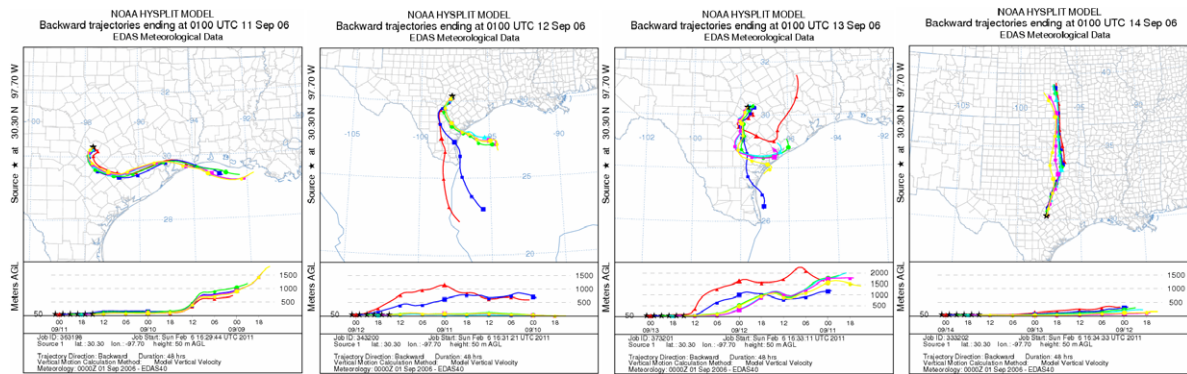


Figure A.1. 10 September to 13 September, 48 h back trajectories ending in Austin, Texas every 2 h between 10 AM to 8 PM.

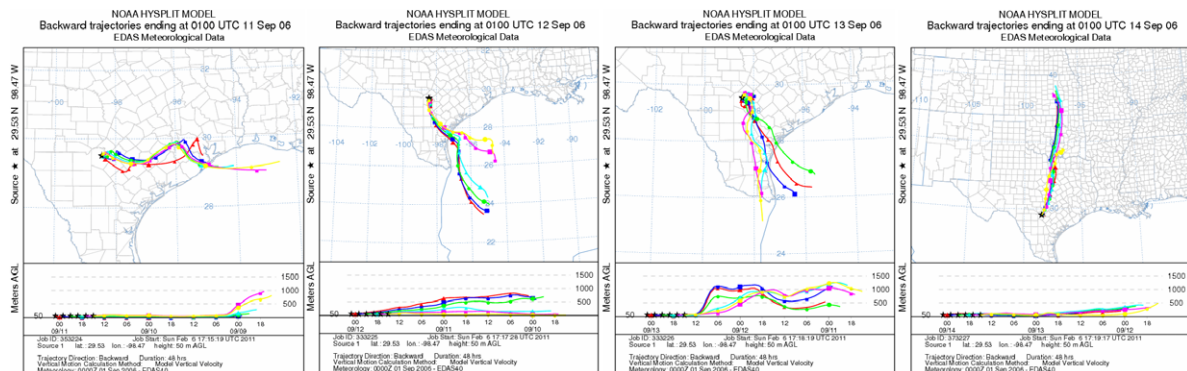


Figure A.2. 10 September to 13 September, 48 h back trajectories ending in San Antonio, Texas every 2 h between 10 AM and 8 PM.

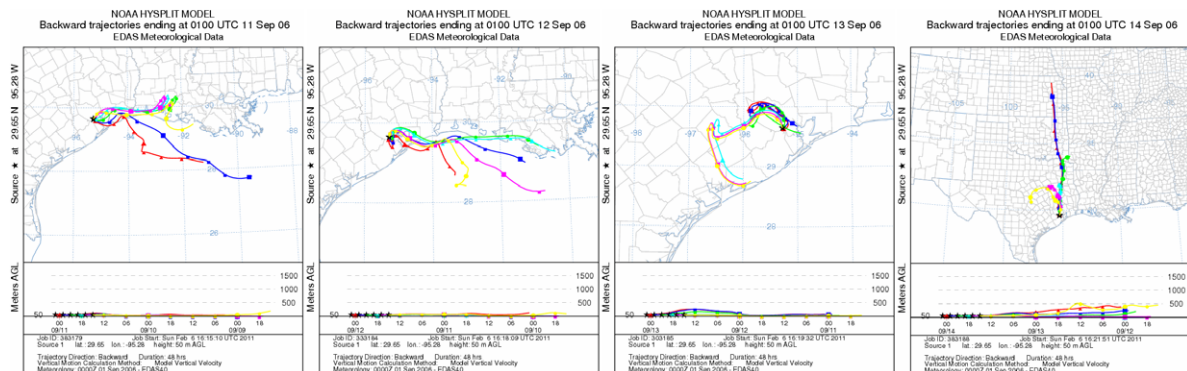


Figure A.3. 10 September to 13 September, 48 h back trajectories ending in Houston, Texas every 2 h between 10 AM and 8 PM.

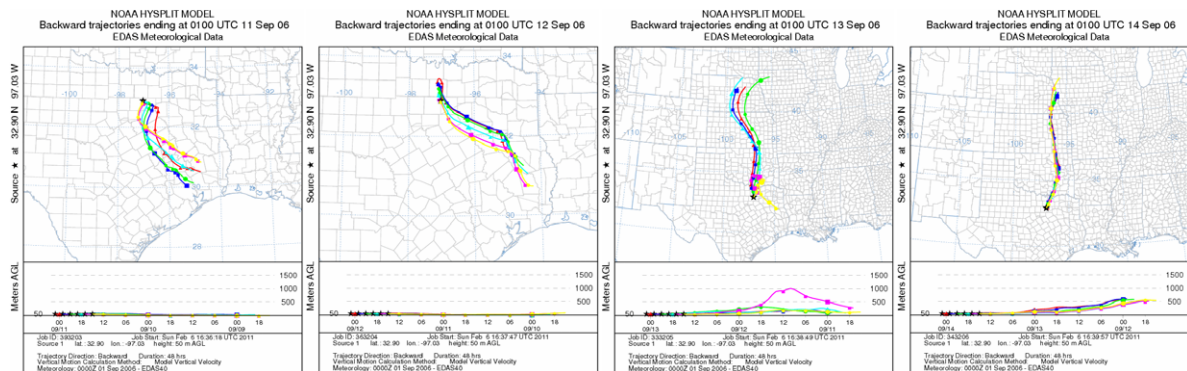


Figure A.4. 10 September to 13 September, 48 h back trajectories ending in Dallas, Texas every 2 h between 10 AM and 8 PM.

6 PM and 8 PM to show how the wind changed throughout the period of the day when high ozone is typical.

Appendix B. Impacts on 8 h average ozone, of PHEV charging at each monitor

Figures B.1–B.7 show the impact of PHEVs on 8 h average ozone concentrations, for each scenario, throughout the modeling period. In most cases, the charts below look almost identical to the charts presented in the text. The one exception is figure B.1, the impacts for the Clinton Monitor in Houston (figure B.1).

Clinton monitor is located in downtown Houston, in close proximity to several major power plants as well as the Houston Ship Channel, location of many of the area's major VOC sources and non-EGU industrial NO_x sources. Therefore the Clinton site is atypical in that it is strongly influenced by local, non-EGU industrial NO_x and VOC sources.

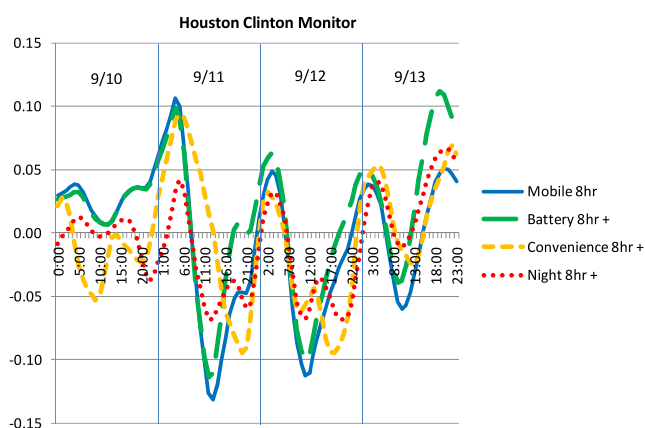


Figure B.1. Time series of impacts to the 8 h average ozone concentration at Clinton monitor (Houston) due to NO_x emissions changes associated with charging and driving PHEVs.

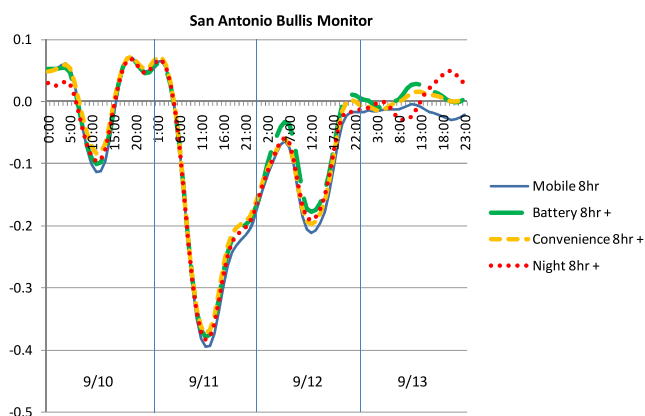


Figure B.2. Time series of impacts to the 8 h average ozone concentration at Bullis monitor (San Antonio) due to NO_x emissions changes associated with charging and driving PHEVs.

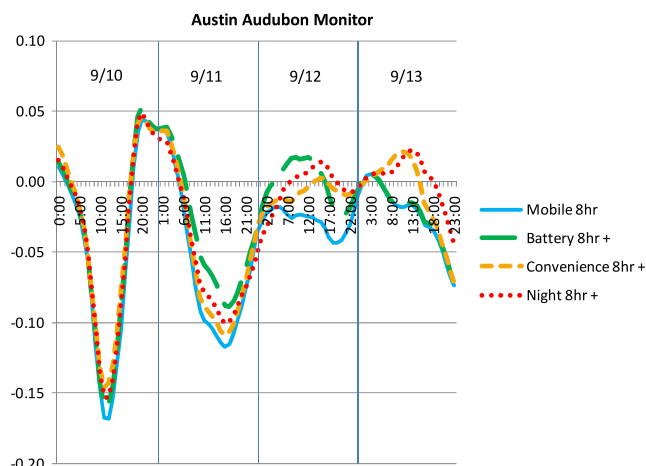


Figure B.3. Time series of impacts to the 8 h average ozone concentration at Audubon monitor (Austin) due to NO_x emissions changes associated with charging and driving PHEVs.

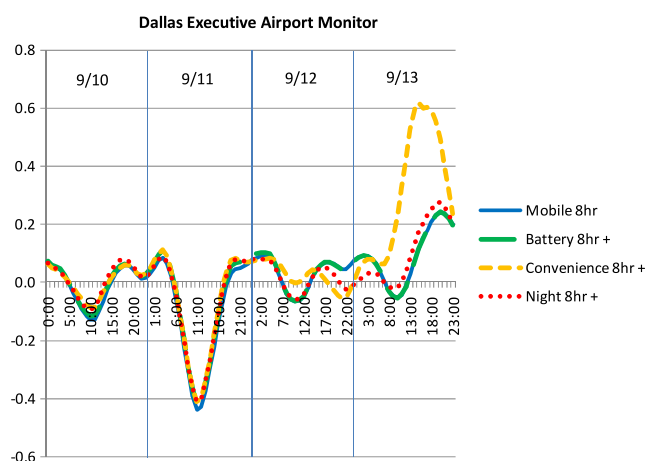


Figure B.4. Time series of impacts to the 8 h average ozone concentration at Dallas Executive Airport monitor due to NO_x emissions changes associated with charging and driving PHEVs.

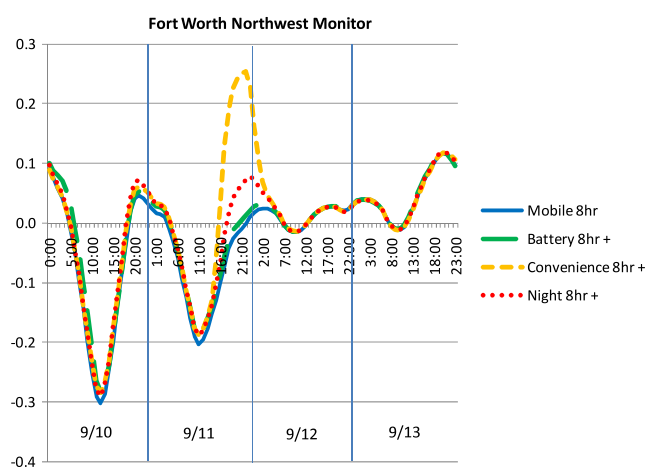


Figure B.5. Time series of impacts to the 8 h average ozone concentration at Fort Worth Northwest monitor due to NO_x emissions changes associated with charging and driving PHEVs.

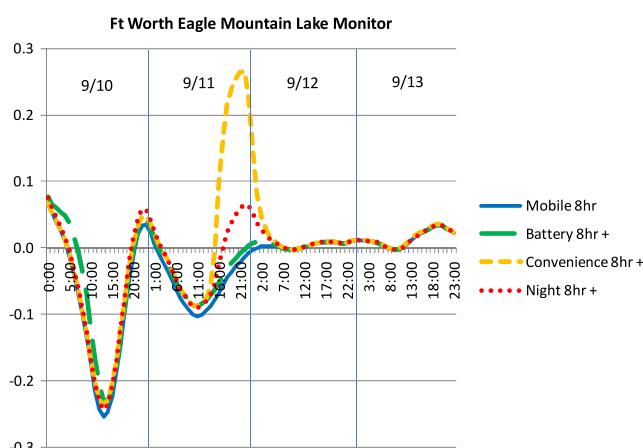


Figure B.6. Time series of impacts to the 8 h average ozone concentration at Fort Worth Eagle Mountain Lake monitor due to NO_x emissions changes associated with charging and driving PHEVs.

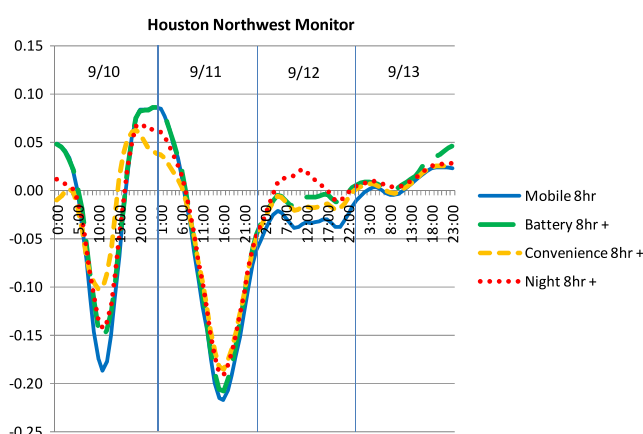


Figure B.7. Time series of impacts to the 8 h average ozone concentration at Houston Northwest monitor due to NO_x emissions changes associated with charging and driving PHEVs.

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